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Embedding a Field Experiment in Contingent Valuation to Measure Context-Dependent Risk Preferences: Does Prospect Theory Explain Individual Responses for Wildfire Risk?

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Abstract

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JEL Classification: Q51, C93, D81
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Introduction

When stated preference approaches are used to elicit willingness-to-pay in probabilistic contexts, modeling underlying individual risk preferences based on expected utility (EU) would lead to biased welfare estimates if in fact risk preferences are not consistent with expected utility (e.g. Jindapon and Shaw 2008, Shaw and Woodward 2008, Riddel and Shaw 2006). EU-based welfare measures would either overstate or understate predicted net social net benefits of a proposed policy depending on how much true risk preferences deviate from linear risk preferences and the direction and the magnitude of shifts in probabilities brought about by the policy. Deviations from expected-utility theory have serious implications for the application of contingent valuation (CV) to a variety of contexts in which policy outcomes are probabilistic, such as policies that address climate change, morbidity and mortality from exposure to environmental toxins, and loss due to catastrophic events. To date, however, few studies attempt to explicitly incorporate non-expected utility (non-EU) theory into CV methods. This paper contributes towards the development of an approach that would generate welfare measures that accommodate non-EU risk preferences. In particular, we combine the empirical approach from Harrison et al (2006) with CV methodologies. Based on prospect theory, this approach allows us to estimate parameters of an indirect utility function and of a probability weighting function for a representative individual, an approach that accounts for individual characteristics as determinants of preferences over risk and utility.

Research published in other literatures suggests that people who understand the probability of wildfire occurrence and the extent of their losses, should wildfire occur, nevertheless choose not to invest in wildfire preparedness (Nelson et al 2005, Cortner and Gale 1990, Schulte and Miller 2010). This is indicative of risk-seeking behavior among property owners facing wildfire risks, and the observation fits well with the prediction of prospect theory (Kahneman and Tversky 1979; Tversky and Kahneman 1992) where a convex utility curve is assumed in loss space. This implies that the property owner prefers a "gamble" (i.e. betting on the chance that a wildfire will not occur or, should it occur, the damage will be small) to a "sure loss" in terms of expenditures on investments to mitigate wildfire risks.

Moreover, for any one property owner, even in parts of the U.S. that are deemed to be at 'high risk' of wildfire, the loss of a home from wildfire is a low-probability high-consequence event, a situation in which the conditions of EU theory are potentially violated (Shaw and Woodward 2008). An unbiased measurement of individual willingness-to-pay for wildfire risk mitigation is necessary for public policies to encourage efficient levels of private investment. Therefore, in this paper, we model property-owners' risk preferences regarding wildfire risks in a non-EU framework. We apply prospect theory (Kahneman and Tversky 1979; Tversky and Kahneman 1992) because it fits well with the observation and also because it accommodates subjective, non-linear transformation of objective probabilities.

An extensive literature in non-EU theory includes empirical work in which laboratory or field experiments are typically used to collect data to measure individual risk preferences (Harrison and Rustrom 2009, Shaw and Woodward 2008). However, development of elicitation methods that are consistent with non-EU theory and CV formats appears to lag behind. Elicitation methods used in the experimental literature are generally context-free and based on lotteries with monetary gains and losses. On the other hand, CV formats require that the contexts in which the respondents rate the policy in question to be explicitly defined in the elicitation material. In comparing across laboratory experiments and survey-based WTP elicitation methods, several authors report that measures of risk preferences are not stable across elicitation methods (Hey, Morone and Schmidt 2009) and, further, not stable across types of gambles (Anderson and Mellor 2009). In the prospect-theory framework, as Wakker (1994) point out, the utility for a good is independent of risk preferences, while individual preferences over probabilities are context-dependent. Thus it is not correct to assume that context-free risk preference parameters can be applied to a specific context, as in Nguyen and Leung (2009). Because risk preferences have been shown to be context dependent, that future CV survey's should included context-dependent measures of risk preferences.

To combine the merits of the two elicitation approaches, in our application, we use a survey with willingness-to-pay elicitation questions written in a lottery-like format, where a hypothetical situation is described to closely resemble the actual policy context. Consequently, the use of covariates becomes important in determining what individual characteristics explain deviations from population risk preferences. In a valuation context, risk preferences typically vary substantially across individuals and their determinants are of interest to policy makers, especially where programs may be developed to target specific groups. Leiter and Pruckner (2009), for example, find that willingness to pay for a program that would reduce the risk of being killed in an avalanche is sensitive to the level of avalanche probability only when individual characteristics are controlled for. In our application, we allow the parameters of the indirect utility function and the probability weighting function to vary across individuals, as is done by Nguyen and Leung (2009) and Harrison (2006). We further claim that, because we are interested in context-dependent risk preferences, additional econometric modification is necessary to account for the differences in how the context is perceived by different individuals. Therefore, in our application, we include "utility shifters" or additive terms in the indirect utility function that vary with individual characteristics. While inclusion of additive terms in an indirect utility function is a standard procedure in the valuation studies (Haab and McConnell 2002), we are not aware of a study where utility shifters are included even when risk parameters are allowed to vary across individuals. We apply the proposed elicitation and estimation approaches to estimate the risk preferences of homeowners that face probabilistic wildfire risks and an investment option that reduces losses due to wildfire.

Probabilistic wildfire risks and willingness to pay to reduce losses

The severity and size of wildfires on public lands in the United States have increased steadily over the past decades, with a corresponding increase in wildfire suppression costs (Stephens and Ruth 2005, Calkin et al 2005, Gebert et al 2005, Gebert et al 2007, Westerling et al. 2006, GAO 2004, GAO 2007). Prior decades of over-suppression of wildfires have contributed to this trend: the amount of fuels is greater than what would have otherwise accumulated so that wildfires that ultimately burn are larger, hotter and more difficult to control. An average of 1,642,000 ha of federal and state managed public lands in the US burned annually between 1960 and 2003; however by the last 5 years of this period, 2,271,000 ha burned annually (Stephens and Ruth 2005). The U.S. Forest Service and Bureau of Land Management exceeded their wildfire suppression budgets every year for the 14 years leading up to 2003 (GAO 2004), with expenditures surpassing a billion dollars per year in four out of the seven years leading up to

2006 (Gebert et al 2008). To the extent that these expenditures have increased faster than overall agency budgets, they crowd out land management activities that include pre-fire fuel reduction, a situation that further escalates wildfire suppression costs.

Another factor contributing to the escalation of wildfire suppression costs is residential development bordering public wildlands, along with a federal mandate that requires firefighting strategies to prioritize protection of private property second only to human safety (Calkin et al. 2005). Wildfire suppression strategies on lands adjacent to residential areas are complex, involve higher levels of risk to human safety and therefore are more expensive than fighting wildfires on open lands. However, private property-owners' investments in fire-retarding landscaping and structural retrofits can check the speed and extent of wildfire spread and improve the effectiveness of firefighting efforts. These investments benefit the property owners, neighboring property owners through spillover effects, and society through reduced wildfire suppression costs (Shafran 2008, Lankoande and Yoder 2006, Butry and Donovan 2008). Lankokande and Yoder (2006) estimated a rate of return for wildfire suppression expenditures of 112% and a rate of return for pre-fire preparedness expenditures of 376%. Lankokande and Yoder conclude based on their analysis that additional funds used for pre-fire preparedness could lower the overall cost of wildfire to society. Accordingly, public programs including the Firewise Communities Program supported by multiple federal agencies, California's Fire Safe Councils, and Nevada's Living with Fire have been established to increase the level of private investment by providing informational, technical and financial support to property owners.

A common observation, however, is that private property owners tend to invest less than what would appear to be in their own best interest in fire-safe actions (Brenkert-Smith, Champ, and Flores 2006; Winter and Fried 2000; Winter, Vogt, and Fried 2002). Several potential reasons have been suggested. First, wildfire suppression costs accrue to public agencies and reduction of these costs is not likely internalized by private homeowners, thus resulting in private underinvestment relative to socially optimum levels. In addition, Kobayashi, Rollins, and Taylor (2010) show that ranchers using public rangelands underinvest in effort to reduce wildfire risk, which increases the threat of wildfire affecting residences on nearby lands. Second, in addition to the cost externality, physical externalities or spillover effects of fire-safe actions on one property to neighboring properties can result in a suboptimal community-level fire-safe outcome (Butry and Donovan 2008; Shafran 2008). Third, occurrence, spread, and severity of wildfire are probabilistic, and risk preferences of individual property owners can affect their fire-safe investment decisions. This paper specifically investigates individual risk preferences using information about property-owners' stated willingness to invest in improvements to reduce property losses in the event of a wildfire.

Modeling Approach

We start by considering the options available to a homeowner who faces a known probability *p* of wildfire affecting her property within the year. In the event of a wildfire, she will bear known loss d_0 ($d_0 \leq 0$). If no action is taken to mitigate the loss, she incurs no cost when there is no fire. She has the option of paying $-c$ ($c \leq 0$) for fire preparedness that would, in the case of fire, reduce her loss to d_1 ($d_0 \leq d_1 \leq 0$). In the case of no fire, with the probability of 1-*p*, the loss to the homeowner is *c*, the cost of the investment. The homeowner has two options: (1) do not to invest and bear no loss as long as a fire does not occur, and bear loss d_0 should fire occur, or (2) invest and bear "sure" loss of *c* in both states of nature with an additional loss of d_1 should fire occur. Using the terminology of Kahneman and Tversky (1979) the two prospects (with and without investment) considered here are negative prospects, i.e. both outcomes of the two events (fire and no fire) are non-positive.

Risk attitudes are jointly determined by the utility function $v(x)$, $x \leq 0$, and a probability weighting function $w(p)$ w, which accommodates nonlinear preferences in probabilities. Following Kahneman and Tversky (1979), the prospective utility for each of the two cases is constructed as:

(1) $V_0 = v(0) + w(p)[v(d_0) - v(0)]$ (no investment)

(2) $V_1 = v(c) + w(p)[v(c + d_1) - v(c)]$ (with investment)

in which $w(p)$ serves as a decision weight placed on the outcome with the larger loss, d_0 in (1) and $c + d_1$ in (2). A higher weight indicates greater aversion to probabilistic risk for a sufficiently small probability (Wakker 1994). A psychological interpretation of the prospective utility formulation is that, for prospect (2), the "gamble" offers a sure disutility of $v(c)$, with a chance $w(p)$ to incur an additional disutility of $v(c + d_1) - v(c)$ (Gonzalez and Wu 1999).[1]

Form of the probability weighting function $w(p)$

Observed subjective transformation of objective probabilities is typically of an inverse-S shape (Kahneman and Tversky (1979); Gonzalez and Wu 1999), and such a curve is commonly specified in estimating *probability weighting function* $w(p)$. The shape and position of an inverse-S-shaped $w(p)$ also have corresponding psychological interpretations, namely "sensitivity" and "attractiveness." They can be more easily explained with specific functional forms of $w(p)$. We consider two functional forms of $w(p)$ that are adopted in the literature (e.g.

[1] Prospect theory does not require $w(p) + w(1 - p) = 1$. Kahneman and Tversky (1979) claim the condition of "subcertainty," $w(p) + w(1 - p) < 1$, is "an essential element of people's attitudes to uncertain events" and more consistent with actual observations.

Tversky and Kahneman 1992; Gonzalez and Wu 1999; Etchart-Vincent 2004) in specifying equations (1) and (2):

(3) $$w_a(p) = \frac{p^\gamma}{[p^\gamma + (1-p)^\gamma]^{\frac{1}{\gamma}}}$$

(4) $$w_b(p) = \frac{\delta p^\gamma}{\delta p^\gamma + (1-p)^\gamma}.$$

As illustrated in Figure 1, both functions are inverse-S shaped provided 0<γ<1 and thus account for the observation of overweighting $(w(p) > p)$ of small probabilities and underweighting $(w(p) < p)$ of large probabilities. $w_b(p)$, however, is less restrictive than $w_a(p)$: parameter γ in $w_a(p)$ regulates both the curvature and the position (or elevation) of the probability weighting function, while in $w_b(p)$ parameter γ regulates the curvature and δ the position of the function. Figures 1 through 3 illustrate the shape of each function for different values of parameters γ and δ.

Curvature represents the psychological principle of "diminishing sensitivity," where the impact of a loss diminishes with distance from the reference point, at either probability 0% or at 100% in this case (Tversky and Kahneman 1992). In Figures 1 through 3, this is seen in that the curves are steeper for smaller and larger probabilities and flatter for mid-range probabilities. Figure 2 illustrates how diminishing sensitivity changes with the value of γ in $w_a(p)$. Relative to linear preferences over probability (the 45 degree line) lower values for γ cause the weighting function to be more horizontal, so that it crosses linear preferences at lower probabilities and represents greater overall deviation from linear preferences. This implies that changes in probabilities are more heavily weighted close to the reference points and are less heavily weighted elsewhere (Gonzalez and Wu 1999). On the other hand, higher values of γ bring the curve closer to linear probability preferences characteristic of expected utility theory.

The position of the probability weighting curve, that is, the absolute level of $w(p)$,describes the "attractiveness" of the gamble.[2] A higher decision weight $w(p)$ implies that the gamble is considered to be more attractive for a positive prospect. In the case of a negative prospect, the interpretation is reversed: a lower $w(p)$ implies a more attractive gamble. Figures 2 and 3 graphically illustrate the relationship between the position of the $w(p)$ curves and the valuation of objective probability. For a fixed level of γ, curves that are positioned higher have wider ranges of probability that are overweighed ($w(p) > p$) than those positioned lower. For a negative prospect this can be interpreted as a higher $w(p)$ curve being associated with higher probabilistic risk aversion, all else equal. In $w_a(p)$ a higher value of γ "elevates" the curve. In $w_b(p)$, however, the position of the curve is regulated separately by parameter δ and, for a given level of γ, a higher value of δ elevates the curve. Thus, there is a clear difference between equations (3) and (4) in terms of flexibility in treating the two psychological concepts (sensitivity and attractiveness). Note that γ =1 and δ =1 reduce each curve to a straight line.

Covariates used in empirical applications to estimate γ and δ control for individual differences in risk attitudes. For example, a tendency toward linear preferences over probabilities may be related to years of education, or previous experience. However, these covariates are distinct from those used to control for how individual differences affect utility. In experimental settings, individual differences in utility are essentially controlled for by elicitation of risk preferences using choices over lotteries with different probabilities of money gains and losses.

Form of the utility function, $v(x)$

While expected utility theory deals with utility over wealth, prospect theory focuses on utilities of gains and losses from some reference level of utility. A common approach is to assume

[2] The position of $w(p)$ also gives rise to the possibility of "subcertainty" or $w(p) + w(1-p) < 1$. In $w_a(p)$, 0<γ<1 implies subcertainty. In $w_b(p)$, δ<1 implies subcertainty while δ>1 implies supercertainty or $w(p) + w(1-p) > 1$.

constant relative risk aversion (CRRA); however, observations are also abundant that are inconsistent with CRRA (Holt and Laury 2002). Accordingly, we consider two functional forms for utility function $v(x)$. The first assumes CRRA as suggested by Tversky and Kahneman (1992) and the second is the more flexible Expo-Power function (Saha 1993; Holt and Laury 2002). For the domain of losses ($x \leq 0$), where x represents c, c+d_1 and d_0, depending on the choice and outcome, the two functions are given as:

(5) CRRA $v_a(x) = -(-x)^\beta$

(6) Expo-Power $v_b(x) = -\frac{1-e^{-\alpha(-x)^\beta}}{\alpha}$.

Since our context is defined for the domain of losses, the interpretations of these functional forms are modified. For $\beta < 1$, both curves are convex, with positive first and second derivatives. This implies that, just as marginal utility diminishes for a risk-averse individual in the gain domain, marginal disutility diminishes as losses increase in absolute terms. Thus, a risk-seeking attitude is assumed over losses, where the risk premium is negative. In equation (6), for a given value of β, smaller α increases the absolute value of $v_b(x)$ (i.e. increase the disutility levels), as illustrated in Figure 4.

Empirical model

Our empirical question is: under what conditions would an individual be willing to pay for wildfire preparedness? That is, under what conditions does investment increase prospective utility? Our empirical models are developed based on the prospective utilities (1) and (2). In an empirical formulation following a random utility approach, the researcher would consider equations (1) and (2) as a deterministic and observable component of utility that is separable from a non-observable component, which is treated as a random error (e.g. Haab and McConnell 2002). However, respondents may make errors in forming prospective utility, in comparing prospective utilities, and in making choices among options (Harrison 2006). Since the observer cannot distinguish between sources of error, we assume additive error terms ε_0 and ε_1 to the prospective utility V_0 and V_1, respectively, that incorporate both respondent error and measurement error.[3] For a symmetric probability distribution of ε, where $\varepsilon = \varepsilon_1 - \varepsilon_0$, the probability of an individual willing to take the fire-preparedness option (i.e. the probability of a 'yes' response to the option) is characterized as:

(7) $Prob('yes') = Prob(V_1 + \varepsilon_1 > V_0 + \varepsilon_0) = Prob(\varepsilon < V_1 - V_0)$.

Equation (7) does not include an "intercept term" that varies with covariates, a typical assumption of risk preferences with experimental data. Because we are interested in how individual characteristics may be associated with utility or disutility from the fire-preparedness investment that is additional to disutility they receive from the financial losses, we consider alternative versions of the utility functions in equations (5) and (6), where "utility shifters" are included:

(8) $u_{jk}(x) = \boldsymbol{\theta}_j \boldsymbol{Z} + v_k(x)$, j=0,1, k=a,b,

where $v_a(x)$ and $v_b(x)$ are defined in equations (5) and (6), $\boldsymbol{Z}$ is a vector of individual characteristics, and $\boldsymbol{\theta}_1$ and $\boldsymbol{\theta}_0$ are the marginal effects of individual characteristics with and without wildfire preparedness investment, respectively. This specification results in prospective utilities $\tilde{V}_0 = \boldsymbol{\theta}_0 \boldsymbol{Z} + V_0$ and $\tilde{V}_1 = \boldsymbol{\theta}_1 \boldsymbol{Z} + V_1$, where V_0 and V_1 are defined in equations (1) and (2). The probability of a 'yes' response in equation (7) is accordingly modified:

[3] Methods to address errors are suggested (Fechner 1966; Luce 1959) and commonly adopted (e.g. Bruner 2009). However, estimates of utility function parameters can be sensitive to the specification choice of error structures (Wilcox 2008, 2009; as cited in Harrison 2006). The sensitivity was confirmed with our dataset, and thus we do not attempt to explicitly address this type of error in this study.

$$(9) \qquad Prob('yes') = Prob\left(\tilde{V}_1 + \tilde{\varepsilon}_1 > \tilde{V}_0 + \tilde{\varepsilon}_0\right) = Prob(\tilde{\varepsilon} < \boldsymbol{\theta Z} + V_1 - V_0),$$

for a symmetric probability distribution of $\tilde{\varepsilon}$, where $\tilde{\varepsilon} = \tilde{\varepsilon}_1 - \tilde{\varepsilon}_0$ and $\boldsymbol{\theta} = \boldsymbol{\theta}_1 - \boldsymbol{\theta}_0$. The coefficient vector $\boldsymbol{\theta}$ thus captures the change in the marginal effects of utility shifters $\boldsymbol{Z}$ with and without making fire-preparedness investment. The rationale for including $\boldsymbol{Z}$ in the model is that individuals may receive more or less satisfaction from investing in wildfire preparedness beyond the utilities from reduced monetary losses depending on their individual characteristics. For example, individual choices would be expected to be influenced by personal experience with wildfire, familiarity and preferences for with wildfire preparedness options, and susceptibility to regret that an individual would feel if the decision turns out to be a wrong one (Weber 2010). Non-monetary aspects of creating defensible space include loss of aesthetic values and the time-cost of maintaining the space. These costs are likely to vary with individual characteristics included in ***Z.***

$P('yes')$ is estimated closely following the procedures described in Harrison (2006). Maximum likelihood estimation is used with an assumption of normally distributed ε, and with error correction for multiple (three) observations for each respondent. All combinations of $w_a(p)$, $w_b(p)$, $v_a(x)$, and $v_b(x)$ are used to construct V_0 and V_1, resulting in four estimation models.

Data and Estimation Procedures

Owners of homes in the 20 communities previously rated as being at highest risk of wildfire in Nevada (Resource Concepts, Inc. 2005) were surveyed in 2006. The communities are located adjacent to public lands that include high desert rangelands throughout the state and higher altitude forests near Lake Tahoe. The majority of survey questions asked about the respondent's residence and wildfire preparedness actions, including whether each item on a fairly complete list of actions had been already taken and if not, whether they would be taken by the homeowner, whether they considered wildfire preparedness to be effective, what prevented the respondent from taking actions, perceived risk of wildfire in the location of their residence, previous experience with wildfire and a number of other attitudinal and demographic questions. The survey resulted in an overall response rate of 19.6%. A total of 1,149 observations from 383 respondents are used in the analyses. Respondents represent a variety of income ranges and a wide variation in other social and demographic characteristics. Table 1 defines and summarizes variables used in this study.

Risk preferences are elicited through several versions of three questions per respondent (one questionnaire version is included in appendix A) regarding respondents' willingness to adopt hypothetical wildfire preparedness investment plans at given costs. Each respondent is presented with a hypothetical probability of wildfire (p) affecting their home during the 2006 wildfire season (approximately June through September), a specified dollar loss in the event of a wildfire if nothing is invested in wildfire preparedness (d_0), and a dollar loss if the investment is made (d_1 such that $d_0 < d_1 \leq 0$). Respondents were asked whether they would invest in wildfire preparedness at three levels of cost (c_1, c_2, c_3), using a 7-point response scale ('Yes!!!' 'Yes!" 'Yes' 'Maybe' 'No' 'No!' 'No!!!'). For this application, we treat 'Yes!!!' 'Yes!" and 'Yes' responses as 'yes' and all other responses as 'no.' The only parameter that changes within an individual respondent's questionnaire is the cost of wildfire preparedness (c_1, c_2, c_3); variation in probability of fire and losses with and without wildfire preparedness occurs across the sample. The data are used to estimate a representative individual's willingness to pay for wildfire preparedness. Variation in risk preferences and other individual characteristics are incorporated through the use of covariates. Each respondent is presented with one of five values for p (1%, 5%, 10%, 20%, and 60%); one of three values of losses d_0 from fire if no investment ($50,000, $100,000, $200,000); and one of five levels of losses if fire d_1 with investment in preparedness ($0, $10,000, $20,000, $50,000, $100,000). The first of the three costs c_1 for wildfire preparedness proposed to each respondent is one of five values ($2,000, $10,000, $20,000, $30,000, $40,000). Two subsequent questions are repeated with alternate payments of ¼ and ½ of initial payment c_1 for c_2 and c_3, respectively.

The survey design is such that for all questionnaire versions the *expected* losses are smaller if wildfire preparedness actions are taken, i.e. $pd_0 < p(d_1 + c) + (1 - p)c$. Thus, if all respondents were risk neutral, there should be no 'no' response to the offer. The data show otherwise: as many as 54% of the observations are indeed 'no' responses, indicating risk-seeking attitude among the homeowners. Further inspection of the data suggests possible inconsistency with expected utility theory. The correlation coefficient between the risk-averse choice ('yes' to a fire-preparedness investment option) and the specified wildfire probability is negative (-0.1471). On the other hand, the correlation coefficient between the risk-averse choice and the cost of damage without action (d_0) ranged between -0.2405 and 0.0658 depending on specified fire probabilities. These correlation coefficients alone do not suggest the data's consistency or inconsistency with CRRA, possibly due to other "lottery" parameters that are not controlled for in the calculation of correlation coefficients.

Estimation Results

Table 2 summarizes the maximum likelihood results to estimate α, β, γ and δ from Equation (7), the specification without covariates, for the four models. The model with $w_a(p)$ and $v_b(x)$ results in unrealistically large $\hat{\beta}$. For the other three models, the hypothesis of all coefficients simultaneously being zero is rejected, and each estimated coefficient is statistically significant.

Estimated β values range between 0.312 and 0.479, confirming convex utility curves, implying that marginal disutility from loss is declining with increasing loss. [4]. In the probability weighing functions, $0 < \hat{\gamma} < 1$ is consistent with an inverse-S shape. Thus we find an indication that EU theory is not consistent with our data. $\hat{\delta}$ in models (2-1) and (4-1) turn out to be relatively large (greater than one), suggesting $w(p) > p$ for a relatively wide range of small probabilities. $\hat{\gamma}$ is higher in models with $w_a(p)$ than with $w_b(p)$. Since γ controls both curvature and elevation of $w_a(p)$, the effect captured by the high value of estimated δ in $w_b(p)$ (i.e. high weights given to the worse outcome) is captured by a higher value of $\hat{\gamma}$ in $w_a(p)$. It is also likely that the same effect captured by $\hat{\delta}$ in models (2-1) and (4-1) is captured by a higher $\hat{\beta}$ value in model (1-1). That is, in model (1-1), without δ separately regulating the elevation of the curve, the disutility of losses due to higher weights placed on worse outcome is captured by higher $\hat{\beta}$ and $\hat{\gamma}$ values.

Inclusion of individual characteristics

Table 3 summarizes the results of equation (9), where the parameters of the probability weighting and utility functions are allowed to vary with respondents' individual characteristics, and utility shifters, $\boldsymbol{Z}$. In this exercise we use *hh_age* (years) and *education* (years) as covariates for utility function parameters α and β, and *experience*, *education* and *publand* as covariates for probability weighting function parameters $\hat{\delta}$ and $\hat{\gamma}$. We include in utility shifters, $\boldsymbol{Z}$, *Tahoe*nature*, a variable to indicate respondent preferences for landscape qualities that are positively associated with wildfire risks (so that some wildfire preparedness actions could result in disutility to residents). The data include respondents with homes in high desert sagebrush areas (sagebrush steppe) and others with homes in the forested mountains near Lake Tahoe.

[4] Under expected utility this would have a risk-loving interpretation. However, this expected utility interpretation of β may not hold in this case because the experimental design did not allow respondents to display risk-adverse preferences. Under prospect theory, there is no need to impose that preferences over probabilities are symmetric.

Because these landscapes are quite different, and people may be more likely to self-select to choose to live in the Lake Tahoe area due to landscape amenity values, we interact *nature* with a Lake Tahoe dummy. We also include *primary* and *regulation* in $\boldsymbol{Z}$ to indicate whether the residence is the respondent's primary home (versus a second home or rental) and the respondent's stated attitude toward the use of regulation to impose wildfire preparedness.

Again, the model with the combination of $v_b(x)$ and $w_a(p)$ performs poorly. In model (3-2) the hypothesis of all coefficients simultaneously being zero is not rejected. As would be expected, the combination of the less restrictive forms for probability weighting and utility, $v_b(x)$ and $w_b(p)$ in model (4-2) performs better than the other three models. For the CRRA models (i.e. without α), *hh_age* and *education* explains $\hat{\beta}$ in a similar manner between the two models (1-2 and 2-2). However, the more flexible Expo-power form with α included to allow for variation in the absolute value of disutility of losses in model (4-2) presents with very different coefficients for these same variables, with opposite signs on *hh_age* and *education* that influence $\hat{\beta}$. In this model, $\hat{\alpha}$ is increasing with *hh_age* and decreasing with *education*. In this case separating the effects of the convexity of the utility function from magnitude of disutility is important. Model (4-2) implies that the level of disutility increases with education and decreases with mean household age.

Turning to the probability weighting function parameters $\hat{\gamma}$ and $\hat{\delta}$, we see little difference between models (2-2) and (4-2). On the other hand, while in model (1-2) with the less flexible form, experience is not significant and the sign on the distance to public lands is negative, the opposite is true for these coefficients in model (4-2), where the inclusion of δ to allow the shape of the curve to vary separately from its height. The distance from public lands negatively affects $\hat{\delta}$, the attractiveness of the gamble. That is, the closer the residence is to public lands (which may enhance a respondent's sense of risk), the more attractive the gamble appears. Prior experience with wildfire is positively associated with the level of $\hat{\beta}$, implying that past experience is related to probability weights that are close to linear and expected utility.

The utility shifters have two sets of effects: direct effect on the utility of each shifter, and indirect effects on the parameters on the probability weighting. We first discuss the direct effects, again ignoring model (3-2). The negative sign on *Tahoe$_*$ nature* is intuitive. Residents who live in the forested areas near Lake Tahoe and indicate that they value the natural environment around their homes, receive less utility from fire preparedness investments. For people who use the home as their primary residence, the investment is more utility enhancing. And utility from wildfire preparedness investments are positively correlated with strength of agreement that such investments should be regulated.

Inclusion of utility shifters changes the parameter estimates of the "original prospective utility" (i.e. V_j instead of $\tilde{\tilde{V}}_j$). Ignoring model (3-2), we see that the mean predicted values of $\hat{\alpha}, \hat{\beta}$ and $\hat{\gamma}$ are comparable to those from the previous models (Table 2), while the level of $\hat{\delta}$ is substantially different. In the model with utility shifters, $\hat{\delta}$ has decreased substantially and is less than unity. Puzzling at first sight, the results are nonetheless explicable. We obtain $\hat{\delta} < 1$ when the utility shifter $\boldsymbol{Z}$ in models (2-2) and (4-2) contains only a constant (results not shown in table). This finding indicates that utility shifters, or even a constant term, capture some important portion of changes in the overall prospective utility $\left(\tilde{V}_1 - \tilde{V}_0\right)$ due to the fire preparedness investment. The total effect of the $\boldsymbol{Z}$ terms in estimation turns out to be positive, capturing prospective-utility-increasing effects of fire-safe investment, net of the change in the original prospective utility $(V_1 - V_0)$. In the original specification (Table 2), the same utility-increasing effects (i.e. risk averse attitude) are captured in the parameters of probability weighting and utility functions. A smaller value of β or larger value of δ produces such effects. Given the relatively stable values of $\hat{\beta}$, it is conceivable that the effects of the ***Z*** terms influence the parameters of the probability weighting function more than those of utility function.

The effect of small and large values of δ on prospective utility is also seen graphically. δ>1 given the estimated values of γ around 0.2-0.5 results in a wide range of overweighed probability $(w(p) > p)$, while the range is much smaller for δ <1 (see Figure 3). Recall that more than half the observations are consistent with risk-seeing attitude ("no" to the investment option) even when the expected losses are reduced by the investment. Once the utility-increasing effects of investment are captured by ***Z*** terms, $\hat{\delta}$ *needs* to be smaller to accommodate risk seeking attitude for a range of (larger) probabilities.

While it is now clear why the models with utility shifters result in smaller values of $\hat{\delta}$, the implication of the differences in $\hat{\delta}$ values between models with and without utility shifters needs to be resolved. Parameter δ determines the range of small probabilities that are overweighted and the range of large probabilities that are underweighted. Therefore, the parameter value itself is of concern to stakeholders and policy-makers. While selection of appropriate estimation model is an empirical question, we find that models without utility shifters can be restrictive in capturing changes in utility between "lotteries" for some applications. While many data collection efforts through experiments control for the contexts in which the lotteries are offered, in real-world applications, the contexts can vary and can be important. We believe that inclusion of utility shifters, as has been done in the valuation literature, is appropriate for our application, and the result from the models with utility shifters – small $\hat{\delta}$ or a wider range of probabilities that are underweighted – seems consistent with the anecdotal evidence that homeowners invest less than anticipated even when they face non-negligible chance of wildfire.

Conclusions and Discussions

In this paper, using survey data with a willingness-to-pay elicitation approach that combines experimental methods developed by Harrison (2006) and CV methods, we empirically estimate risk preferences of private property owners who face wildfire threats in Nevada. We find that the data exhibit inconsistency with predictions of the expected utility theory. Instead, we find that the property owners tend to underweight large probabilities but overweight small probabilities of fires. In a companion paper that analyzes factors affecting actual adoption of fire-safe actions, it is found that actual fire-safe action decisions are importantly associated with individual wildfire risk perception (Kobayashi, Zirogiannis, Rollins, and Evans, 2010). Our estimation results in this paper provide further explanation of how such risk perception may be formed. We also find that risk preferences are associated with individual characteristics of the property owners. Such demographic information is readily available to policy makers, and thus our results will be useful in designing policies to address potential underinvestment in fire-preparedness by private property owners due to their risk preferences. In the case of this application, if expected utility theory been assumed to hold, welfare estimates of polices that target enhancing private investment in wildfire preparedness would be biased.

The observed nonlinear preferences in probabilities are consistent with many other experimental and field observations. In the case of public policies that concern probabilistic outcomes, CV approaches that assume EU may lead to biased welfare estimates. We argue that there is a role for work to incorporate non-EU theoretic approaches in CV, and this current study is a step in that direction. A focus in much of the existing literature has been to control for or eliminate the effect of context on measurement of risk preferences, because it has been shown that such preferences are context-dependent. Wakker (1994) demonstrates theoretically that while utility is independent of preferences over risk, risk preferences are not independent of utility, and several studies empirically confirm this. However, for relevance to CV, context dependency implies that combining risk preference and utility elicitation methods in a policy-relevant context is important.

The context of our application is such that the CV 'good' is willingness-to-pay for dollar-valued losses. This provides us with an ideal situation to apply methods developed in the experimental literature because the dollar valued outcomes allow for isolation of the effect of risk parameters. For future work to be most relevant to CV methods, where estimation of willingness-to-pay is generally for a change in the quality or quantity of a non-market good, this approach will require some other means to isolate the parameters for risk preferences from utility. Finally, these results reiterate the potential gains from incorporating non utility theory and field experiments into applied environmental economics.

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Table 1. Summary Statistics of Variables Used in this Study[a]

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
choices	1 if ‘yes’ to given fire-safe investment plan; 0 otherwise	1149	0.459	0.499	0	1
p	Probability of fire	1149	0.247	0.219	0.010	0.600
d_0	Losses due to fire when no action is taken	1149	-124.935	61.437	-200	-50
d_1	Losses when fire-safe action is taken	1149	-28.460	35.038	-100	0
c	Cost of fire-safe action	1149	-8.661	9.387	-40	-0.063
EL_0	Expected loss without action	1149	-31.569	36.104	-120	-0.500
EL_1	Expected loss with action	1149	-15.962	19.217	-90	-0.250
hh_age	Average age of respondent’s household members in years	366	47.636	17.599	9	75
education	Years of formal education	370	15.424	2.605	9	19
publand	Distance from public land (miles)	377	0.960	1.637	0	5
experience	1 if experience with wildfire; 0 otherwise	383	0.637	0.481	0	1
Tahoe	1 if community near Lake Tahoe; 0 otherwise	365	0.395	0.489	0	1
nature[b]	Love for nature and privacy as a reason for not taking fire-safe action (1 No!! - 5 Yes!!)	323	3.183	0.978	1	5
primary	1 if the high-risk residence is the primary residence	380	0.689	0.463	0	1
regulation	Approve stricter building regulations about fire safety (1 No!! - 5 Yes!!)	363	3.590	0.940	1	5

[a] All monetary values are in thousand US dollars.
[b] Variable created according to factor analysis.

Table 2. Maximum Likelihood Estimation Results without Covariates

($n_{observations}$=1149, $n_{respondents}$=383)

	(1-1)	(2-1)	(3-1)	(4-1)
Utility	$v_a(x)$		$v_b(x)$	
Prob. weighting	$w_a(p)$	$w_b(p)$	$w_a(p)$	$w_b(p)$
α			4.819***	0.139**
β	0.479***	0.312***	102.4***	0.381***
γ	0.510***	0.162***	0.221***	0.182***
δ		1.056***		1.232***
Log pseudo-likelihood	-851.820	-748.111	-785.051	-745.795
Prob > $\chi^2(0)$	0.000	0.000	0.000	0.000

Notes:
Significance levels of 0.01, 0.05, and 0.1 are denoted by three, two, and one asterisks (***, **, *), respectively.

Table 3. Maximum Likelihood Estimation Results with Explanatory Variables

($n_{observations}$=876, $n_{respondents}$=292)

	(1-2)	(2-2)	(3-2)	(4-2)
Utility	$v_a(x)$		$v_b(x)$	
Prob. weighting	$w_a(p)$	$w_b(p)$	$w_a(p)$	$w_b(p)$
α				
hh_age			-0.00912	0.0130***
education			0.0765	-0.0726***
constant			-1.316	0.695***
β				
hh_age	-0.00328**	-0.00369***	-0.00189	0.00505**
education	0.0203**	0.0146*	0.0136	-0.0347**
constant	0.203	0.300**	0.0328	0.800***
γ				
publand	-0.0284	0.0584	-0.193	0.0541
experience	0.025	0.250**	-1.471	0.274**
education	-0.0149	-0.033	0.717	-0.0426
constant	0.686***	0.591	-3.127	0.758
δ				
publand		-0.0461**		-0.0745***
experience		0.0241		0.023
education		-0.0211		-0.0534
constant		0.826*		1.452**
θ				
Tahoe*nature	-0.0129	-0.0588	0.00157	-0.0681
primary	-0.0101	0.0535	-0.0364	0.0617
regulation	0.192***	0.179**	0.170**	0.178**
constant	0.162	0.150	1.174*	0.164
Mean predicted α			-0.570	0.195
Mean predicted β	0.360	0.349	0.152	0.504
Mean predicted γ	0.443	0.297	6.827	0.327
Mean predicted δ		0.470		0.568
Log pseudo-likelihood	-533.5	-521.4	-549.5	-519.9
Prob > $\chi^2(2)$	0.0046	0.0016	0.3053	0.0020

Notes:
Significance levels of 0.01, 0.05, and 0.1 are denoted by three, two, and one asterisks (***, **, *), respectively.

Figure 1. Probability Weighting Function (a) and (b)

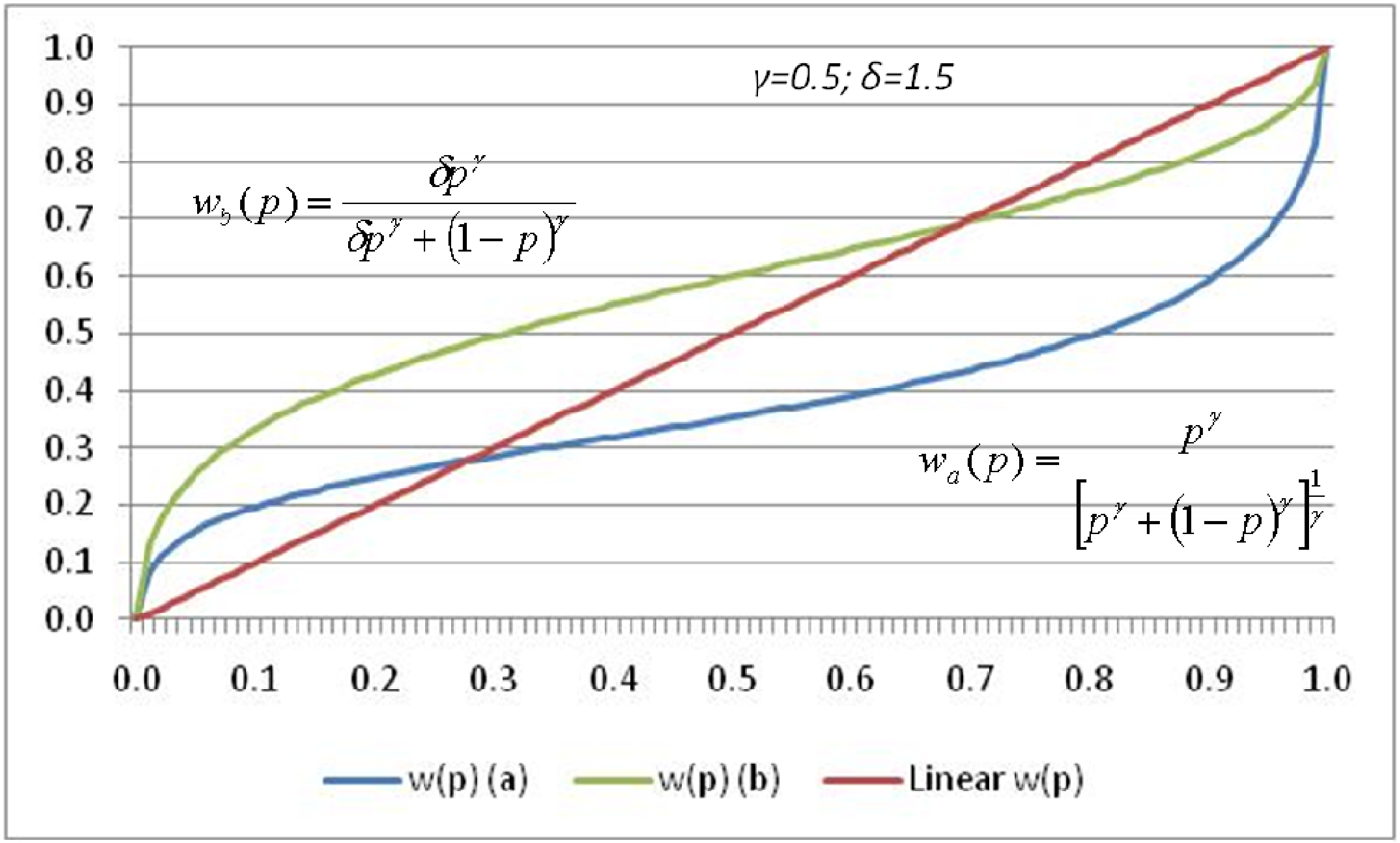


Figure 2. Probability Weighting Function (a)

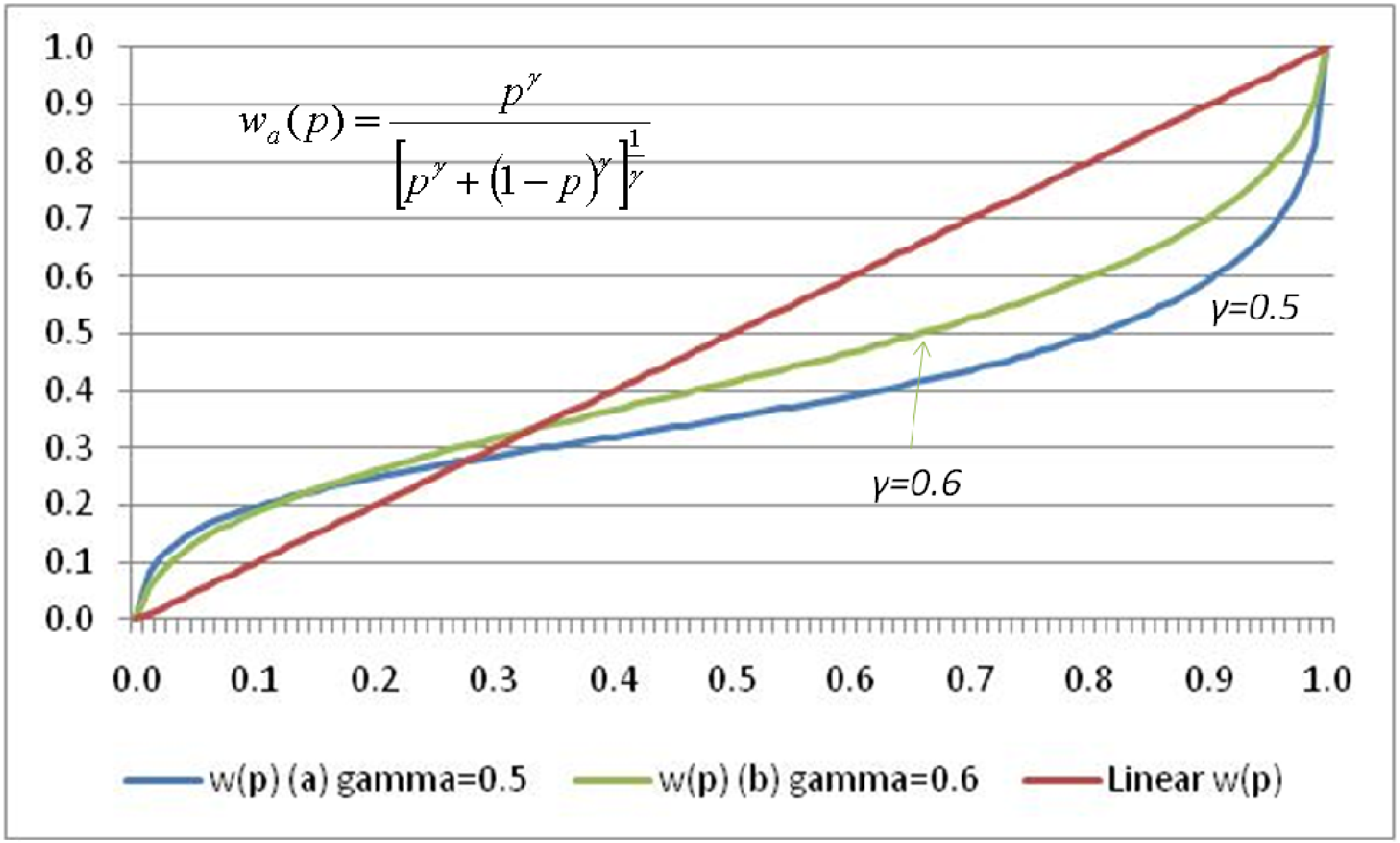


Figure 3. Probability Weighting Function (b)

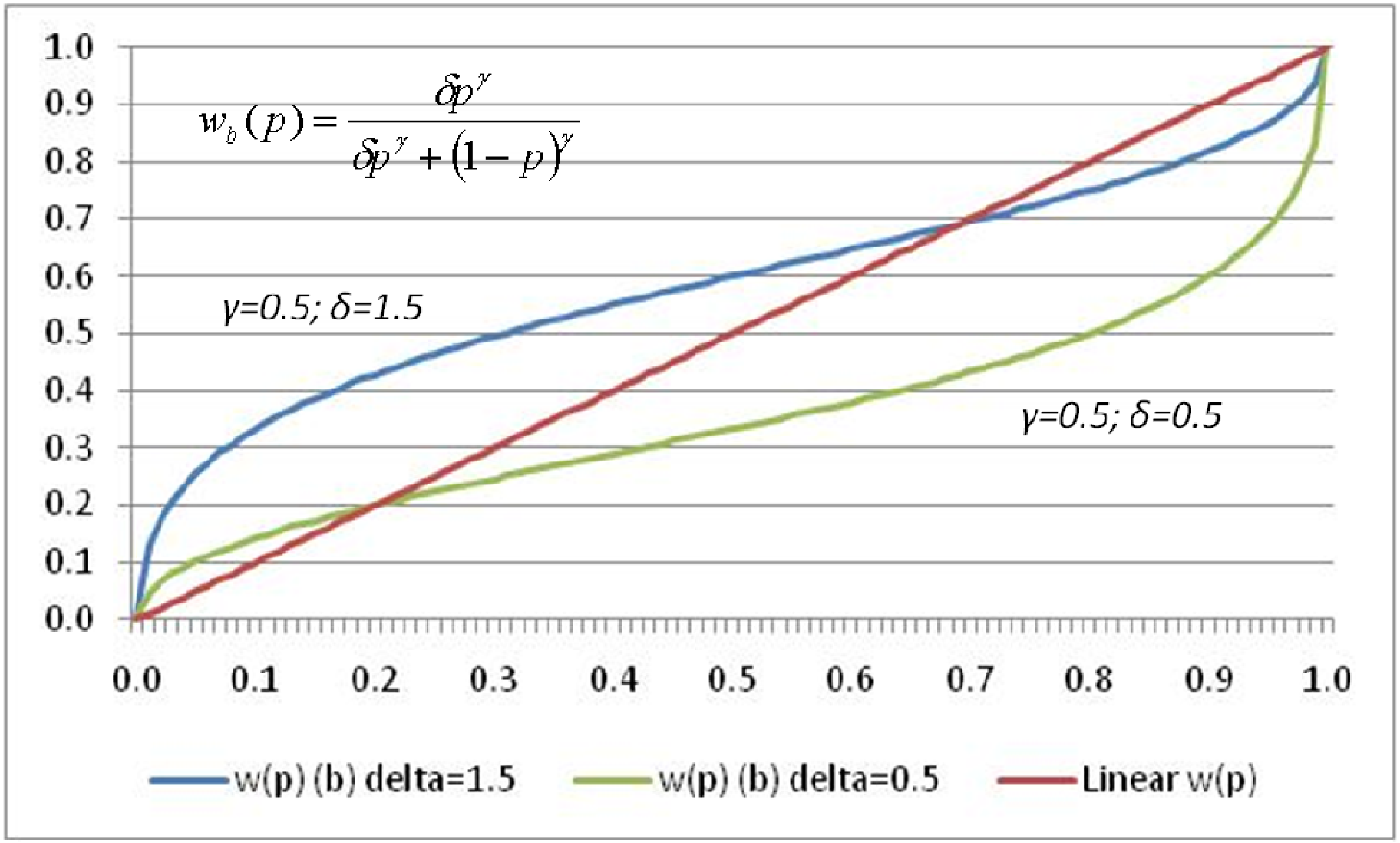
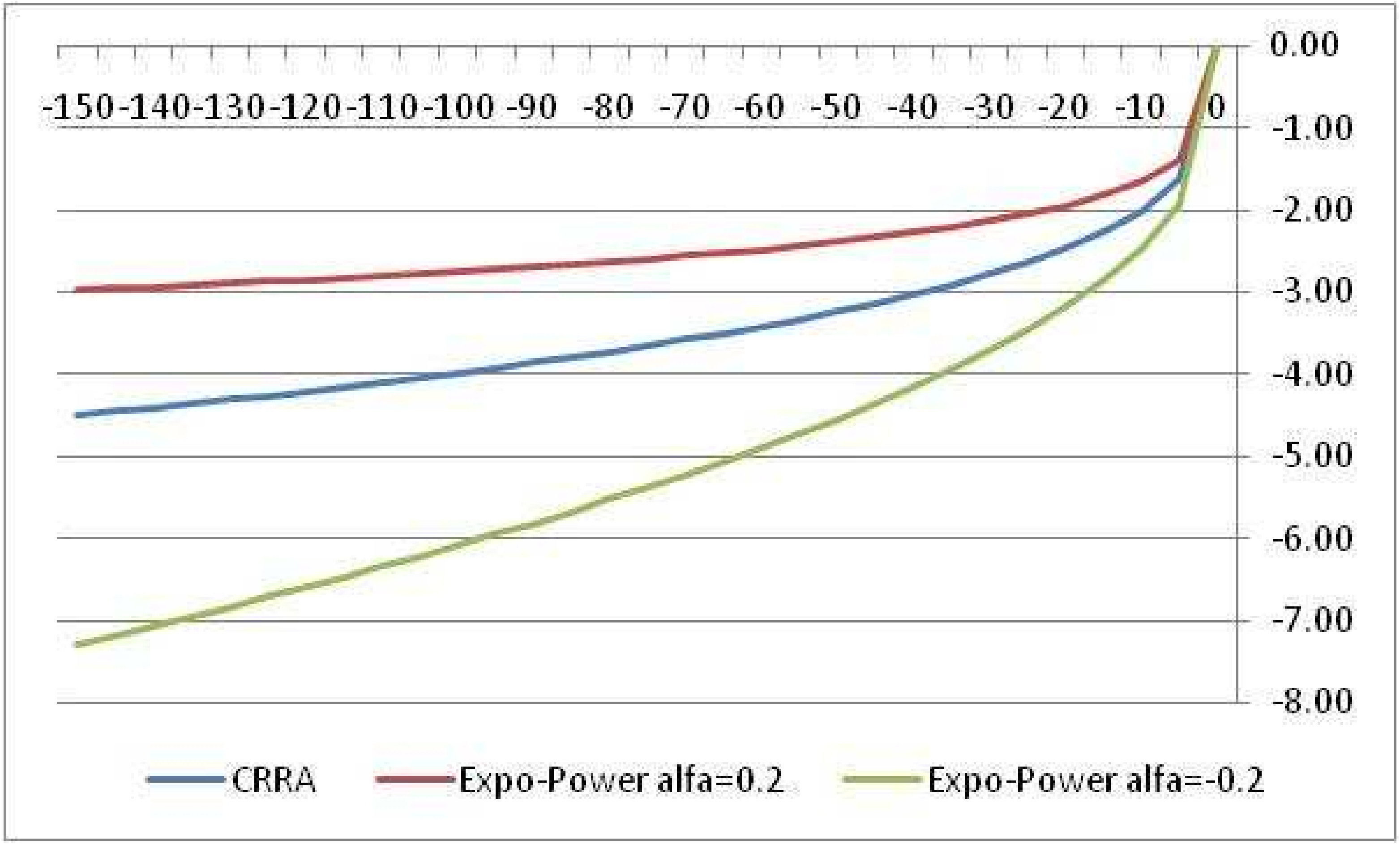


Figure 4. Utility Function (a) and (b)



Appendix: Survey Questions

Suppose that there is a **___A___**% chance of a wildfire in the area near your home during 2006.

Also suppose that if a fire should occur your loss would be **$__B_ if you do nothing else** to reduce the threat to your home.

Finally, suppose that if you **spend $__C__ over the next 4 months on fire safe actions**, your loss from a wildfire **would be reduced to $__D__.**

-

Please use the information above to answer the next three questions.

1. Would you spend **$_C_** over the next 4 months to **reduce your loss** from a possible wildfire from **$__B___** to **$___D___**?

❑ **Yes!!!** ❑ **Yes!** ❑ **Yes** ❑ **Maybe** ❑ **No** ❑ **No!** ❑ **No!!!**

2. Now imagine **a policy** that would provide a **three-to-one match** on what you spend on fire safe actions. For a project that costs **$__C___**, your share would only be **$___1/4 C___**. The other half is covered by the one-to-one match.

In this case, would you spend the **$__1/4C__** to **reduce your loss** from a possible wildfire from **$__B___** to **$___D___**?

❑ **Yes!!!** ❑ **Yes!** ❑ **Yes** ❑ **Maybe** ❑ **No** ❑ **No!** ❑ **No!!!**

3. Now suppose that in order to stretch funds over a larger number of people, the match is one-to-one. . For a project that costs **$__C___**, your share would be **$___1/2C___**. Matching funds would cover the other half.

In this case, would you spend the **$___1/2C______** to **reduce your loss** from a possible wildfire from **$___B____** to **$___D_____**?

❑ **Yes!!!** ❑ **Yes!** ❑ **Yes** ❑ **Maybe** ❑ **No** ❑ **No!** ❑ **No!!!**